RMSprop-Enhanced ResNet152V2 for Automated Plant Leaf Disease Detection

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Abstract

India is a cover crop region where a significant amount of the population is sustained by agricultural output, which is also strongly dependent upon for the country's overall economy. Research indicates that almost 70% of rural households rely on it for livelihood. India is ranked eighth in terms of agricultural exports and second in terms of agricultural output. Still, it achieves the top spot in the world for cotton exports, which significantly boosts the nation's economy. In this script, Plant Leaf Disease Identification using RESNET152V2 Enhanced with Rmsprop Optimization (PLDI-RESNET-RPO) is suggested. The input image is taken from Cotton disease data. Then, the input pictures are fed into preprocessing stage. In preprocessing, Dual Image-adaptive Learnable Filter (DILF) is used to remove the noise present after the input picture. The pre-processed pictures are given into RESNET152V2 for classifying the Plant Leaf Disease as Fresh Cotton Plant, Diseased Cotton Plant, Fresh Cotton Leaf, also Diseased Cotton Leaf. Then the RESNET152V2 is compared with four optimization methods which are collected from various time periods such as Adaptive Gradient (AdaGrad), AdaDelta (AdaD), Mini Batch Stochastic Gradient Descent (MBSGD), Rmsprop optimizer (RPO). By comparing other three optimization algorithms, Rmsprop Optimization (RPO) gives high accuracy which accurately classifies the Plant Leaf Disease. The proposed PLDI-RESNET-RPO technique is applied on Python. Then performance of the suggested technique is compared with other current techniques. The suggested method reaches 25.68%, 22.54% and 31.24% higher accuracy when comparing with existing techniques such as cotton plant leaf disease detection using deep neural networks (CPL-DD-DNN) deep learning model intended for cotton disease prediction by fine-tuning through smart web application in agriculture (DLM-CDP-SWA) and presented Plant leaf disease detection by computer vision also machine learning algorithms (PLDD-CV-MLA) respectively.

Keywords:
Plant Leaf Disease Detection, Cotton disease, RESNET152V2, Rmsprop optimizer.

1. Introduction

India is a horticultural also agricultural nation, with a large section of the population relying solely on farming [1].

*SmartIndustry 2026: 3rd International Conference on Smart Automation & Robotics for Future Industry, March 26-27, 2026, Lviv, Ukraine

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Agriculture not only supports farmers, but it also shows a vital role in overall structure the Indian economy. According to surveys and studies on Indian agriculture, agriculture provides a living for about 70% of rural households [2]. It accounts for over 17% of the country's total GDP (increasing from 17.8% in 2019-2020 to 19.9% in 2020-21) and employs and supports nearly 60% of the population. India ranks second in agricultural product output and ninth in agricultural exports; it explains why agricultural production has increased rapidly over the last fifteen years since $87 to $459, with an annual growth rate of 12%. Many South Asian countries, with Bangladesh, China, also India, rely seriously on agriculture [3]. Because of global warming also climate change, regional crop infections are becoming additional common, resulting in a significant decline in farming productivity. Cotton is the vital cost-effective crops, sometimes identified as "white gold" or "king of fibers". Cotton's worldwide trade value is now $40 billion, but it is predicted to rise to $60 billion by the end of 2030. Bangladesh is the world's second-largest dealer of ready-made garments, and it lately shipped $20 billion in textile items throughout the world [4]. Cotton utilized as a primary source in industrial sector and in rotating mills to manufacture yarn, which is then utilized to make clothing in facilities. Take into account the general size, shape, and color of the plant; the size, distribution, with color of the leaves; the texture and color of the bark, stem, or trunk; and the placement and color of the roots. Additionally, regular occurrences like a healthy plant's leaf dropping should be noted. [5]. In several existing methods there is a limited generalizability of trained models to diverse plant species and disease types is a result of the use of small and biased datasets. Scaling up the disease identification procedure to a large number of plants or fields is challenging due to the limited computer resources and processing capabilities of current approaches. These difficulties in the current method stimulate us to carry out this research work. The novelty of the suggested PLDI-RESNET-RPO method is Plant Leaf Disease Identification based on RESNET152V2 optimized with Rmsprop optimizer.

The main contributions of this proposed method are abridged below:

- In this paper, Plant Leaf Disease detection by RESNET152V2 Enhanced with Rmsprop Optimization (PLDI-RESNET-RPO) is proposed.
- Developing a Dual Image-adaptive Learnable Filter to removes the noise existing in the image.
- RESNET152V2 is to classify the Plant Leaf Disease as Fresh Cotton Plant, Diseased Cotton Plant, Fresh Cotton Leaf, also Diseased Cotton Leaf.
- Then the RESNET152V2 is compared with four optimization methods such as Adaptive Gradient, AdaDelta, Mini Batch Stochastic Gradient Descent, Rmsprop optimizer. By comparing other three optimization algorithms, Rmsprop Optimization (RPO) gives high accuracy which accurately classifies the Plant Leaf Disease.
- Rmsprop Optimization is used to optimize RESNET152V2, which enhance the ordering of plant leaf disease.
- The proposed PLDI-RESNET-RPO technique is related with the existing techniques like, CPL-DD-DNN, DLM-CDP-SWA, and PLDD-CV-MLA respectively.

The remainder of paper is arranged in given below. Literature review presented in section 2, materials and procedures employed article discussed section 3, result also discussion described section 4, and conclusion presented section 5.

2. Literature Survey

Amongst the various research works are deep learning based plant disease identification, the most some present research works were revised here in this segment.

In 2023, Singh, et.al, [6] have presented cotton plant leaf disease finding by DNN. This suggested paper introduces Cotton plant infections can cause a variety of disorders that are difficult for the human eye to detect, from bacterial infections to nutritional deficiencies. The deep learning technique to help detect certain diseases while taking these limitations into account. Despite testing numerous algorithms, CNN turned out to be incredibly productive and efficient. It delivers high accuracy and low precision.

In 2023, Islam, et.al, [7] have suggested DL methods for cotton infection guess by fine-tuning with smart web request in agriculture. This paper suggests a DL-based technique for cotton leaf infection identification by adjusting the deposits and limits of previous Transfer Learning (TL) procedures. Additionally, it looked into how well other fine-tuning TL methods including VGG-16, VGG-19, Inception-V3, and Exception performed for cotton disease forecast by publically accessible cotton data. It provides low computational time and low sensitivity.

In 2022, Harakannanavar, et.al, [8] have presented Using machine learning and computer vision techniques, identify plant leaf diseases. The models of sick tomato leaves are measured in this proposed article. With these disease models of tomato leaves, the farmers would be able to easily diagnose the infections based on the early indicators. The pixels in the leaf samples are first reduced in size in order to develop the value of the tomato samples. The next step is to apply histogram equalization. The K-means clustering technique splits the data space into Voronoi cells. One technique for obtaining the boundaries of leaf samples is contour finding. It offers low RoC and good specificity.

In 2022, Jayaramu, et.al, [9] have presented ESMO-based plant leaf infection documents: a machine learning method. This suggested paper, diagnose plant diseases also stop them from diffusion, machine learning and artificial intelligence technologies are now being studied on plant picture data. By analyzing these plant picture collections, businesses and farmers can raise agricultural productivity and quality. A methodology for disease identity on the leaf image data of rice and cotton plants is proposed in this chapter. A decrease pixel adjacency matrix (SPAM) technique is utilized for attributes removal in the formulation of the suggested methodology. However, to choose the best attributes from the retrieved attributes, the exponential spider monkey optimization approach (ESMO) has developed. It provides high f1-score and high computational time. In 2023, Abd Algani, et.al, [10] have suggested Leaf disease identification and classification using optimized DL. Ant Colony Optimization by Convolution Neural Network (ACO-CNN), a unique DL technique for illness diagnosis and classification, is presented in this suggested study. By ant colony optimization (ACO), the efficiency of disease diagnoses in plant leaves was examined. Color, texture, and plant leaf arrangement geometries are removed from the providing pictures by CNN classifier. It offers low sensitivity and great accuracy.

3. Proposed Methodology

Plant Leaf Disease Identification using RESNET152V2 Optimized with Rmsprop Optimization (PLDI-RESNET-RPO) is depicted in this segment. The block diagram of proposed PLDI-RESNET-RPO for plant leaf disease identification is shown in figure 1.

In figure 1, the input picture is collected from Cotton disease data. The input picture is pre-processed by Dual Image-adaptive Learnable Filter. The pre-processed picture is given into RESNET152V2 for identifying plant leaf disease as New Cotton Plant, Diseased Cotton Plant, Fresh Cotton Leaf, also infected Cotton Leaf. And Rmsprop Optimization is used to optimize the weight parameter of RESNET152V2.

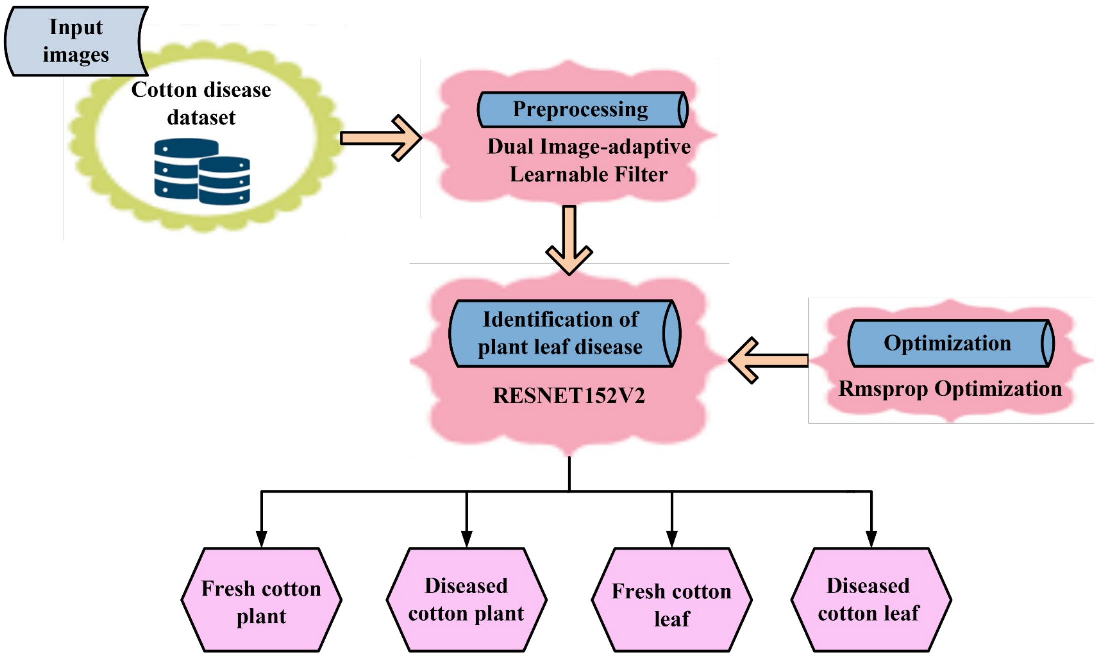

Figure 1: Block Diagram of the Proposed PLDI-RESNET-RPO System I

3.1 Image Acquisition

The input images are collected from a publicly available cotton disease dataset [11], consisting of **2310 images** categorized into four classes: Fresh Cotton Leaf, Diseased Cotton Leaf, Fresh Cotton Plant, and Diseased Cotton Plant. The dataset includes images of various cotton leaf diseases such as **leaf curl, bacterial blight, grey mold, and leaf blight**, captured under different environmental conditions and disease severity levels.

To ensure reproducibility and effective model training, the dataset is divided into three subsets:

- **Training set:** 70% (1617 images)
- **Validation set:** 15% (346 images)
- **Testing set:** 15% (347 images)

All images are resized to 224 × 224 pixels to match the input requirements of the ResNet152V2 architecture. Data normalization is applied by scaling pixel values to the range [0,1]. Additionally, to improve model generalization and reduce overfitting, data augmentation techniques such as rotation, flipping, zooming, and horizontal shifting are applied to the training dataset.

The dataset is balanced across the four classes to avoid bias during training. Each image is labelled according to its respective category, enabling supervised learning for accurate classification. This structured preprocessing and dataset partitioning ensure consistency and reproducibility of the experimental results.

3.2 Pre-processing using Dual Image-adaptive Learnable Filter

In this step, Dual Image-adaptive Learnable Filter (DILF) [12] is used to remove the noise from the collected images. The Dual image-adaptive Learnable Filter improves the quality of pictures by decreasing noise and boosting detail. The filter is meant to be computationally efficient, making it appropriate for resource-constrained applications. The DILF filter is to highlight certain elements and increase image quality without adding distortions or artifacts. A sort of edge-preserving and gradient-preserving picture operation called a guided filter uses the guiding image's object border to determine the saliency of the image. The saliency of the image is calculated as given in equation (1),

$$Fm(q_j) = q_j \times \frac{Fm\infty(q_j)}{\infty(q_j)} \tag{1}$$

Where, F represents the effectiveness value, m represents the noise in the input image, q_j denotes the pixel value, also ∞ denotes the luminance function. Gamma and exposure are just basic power and multiplication changes. These mapping functions are obviously differentiable with regard to their parameters as well as the input image. An input parameter is built into the design of the differentiable contrast filters to control the linear interpolation between the original and completely improved images calculated as given in equation (2),

$$r_j = b_l J_j + c_l \tag{2}$$

Where, r_j represent the size of the image, b represents the linear coefficient, c denotes the normalization value, J denotes the guided map, and l denotes the filter value. The algorithm calculates the true underlying state of the image by using the noisy input images as measurement. In order to generate a more accurate sign of the image, this calculation entails filtering out noise and mistakes in the input images. The normalization value is given in equation (3),

$$c_l = q_l - b_l \varphi_l \tag{3}$$

Where, c_l represents the normalization value, and φ represent the non-zero coefficient. Finally, the noises are removed from the input pictures by using DILF. Then, the pre-processed pictures are served into the classification phase.

3.3 Classification of Plant Leaf Disease using RESNET152V2

In this section, Plant Leaf Disease Classification using RESNET152V2 [13] is discussed. ResNet152V2 has demonstrated a high level of accuracy in picture categorization tests. For precisely categorizing plant leaf diseases based on images, this makes it a good fit. ResNet152v2's 152 convolutional layers have the capacity to individually learn a level's properties. This method expedites the training and covering in order to obtain high accuracy. The spatial interdependence of the ResNet is given in equation (4),

$$x_1 = g(y_1, x_1) + i(y_1), y2 \tag{4}$$

Where, y_1 represents the residual unit weight, x_1 represents the ResNet layer, g represents the loss function, $y2$ indicates observation of each images, and i represents the interdependence. Thus, ResNet layers are part of the plant leaf disease classification model. A plant leaf disease will show regions of opacity or infiltrates caused by insects. These regions may show as patchy or consolidated white or grey spots on the images are calculated as given in equation (5),

$$y_4 = x_1 + g(\beta, \xi) \tag{5}$$

Where, y_4 represents the indicates the hidden state, β represents the input variable, and ξ represents the ResNet layer. The signs of leaf diseases, such as spots, blights, wilting, curling, or mottling, can be used to categorize them. A common fungal illness called powdery mildew causes white, powdery patches on leaves is calculated as given in equation (6),

$$y_j = y_1 + \sum L - 1^{j-1} g(y_l, x_l) \tag{6}$$

Where, j represents the convolutional layer, L represents the learnable constant values, and l represents the dynamic adjacency in image pixel matrix. Plant leaf diseases can also be kept from spreading and becoming more severe by employing disease-resistant plant kinds and keeping an eye out for early warning indicators. In order to stop the illness since dispersal to other plants, it's critical to remove and discard infected leaves from affected plants as soon as possible and to maintain good cleanliness is calculated as given in eqn (7),

$$\frac{\wp \lambda}{\wp y_1} = \frac{\wp \lambda}{\wp y_j}\left(1 + \frac{\wp}{\wp y_1} \sum L\right) \tag{7}$$

Where, $\wp$ represents the learnable hyper parameters, and λ represents the adjacency matrix. Finally, RESNET152V2 identifies the Plant Leaf Disease successfully as New Cotton Plant, infected Cotton Plant, Fresh Cotton Leaf, and infected Cotton Leaf. Due to its practicality and relevance, the artificial intelligence-based enhancement approach is considered in the PLDI-RESNET-RPO identified. In this work, AdaGrad, AdaD, MBSGD, and RPO are compared to find which optimization accurately identifies the Plant Leaf Disease. Optimize the PLDI-RESNET-RPO optimum parameters $\wp \& \xi$. Here, the following procedure is applied to alter the bias and weight parameters. of RESNET152V2.

3.4 Optimization

The weight parameter $\wp \& \xi$ RESNET152V2 is optimized using the following methods. The weight parameter $\wp$ is optimized to increasing the accuracy and ξ is optimized to decreasing the computational time

3.4.1 Adaptive Gradient

In this section, Adaptive Gradient (AdaGrad) [14] is discussed. It is well known that adaptive gradient algorithm converge more quickly than conventional gradient descent techniques. This may lead to shorter training durations and enhanced learning algorithm performance overall. A common nonconvex optimization issue is the optimization of displaced sub arrays, where the variables are the sub array center $y\, and\, z$. The field of the G sub's primary lobe is represented by φ. The notation for the fitness function is $f(y,z)$. Fitness function is weighted as given in equation (8),

$$f(y,z) = \beta \max\left|F_{arr}(v,w,y,z)\right| + (1-\gamma)S\,LL \tag{8}$$

Where, y represents the position value, z represents the efficiency, f represents the aperture value, β represents the gradient value, F represents the array element, v represents the velocity, w represents the variable, γ represents the layer of gradient, and SLL represents the side lobe level. The fitness function's gradient matrix in relation to the enhanced variables is necessary for gradient search method to work. Regarding the radiation pattern as given in equation (9),

$$w_y = \frac{\alpha \max\left|F_{arr}(v,w,y,z)\right|}{\alpha y} \tag{9}$$

Where, w_y represents the radiation pattern, and α represents the constant parameter.

3.4.2 AdaDelta

In this section, AdaDelta (AdaD) [15] is discussed. The AdaDelta optimization method's parameters have individual learning speeds that progressively drop until the learning process can no longer be carried out. The updating of parameter is given in equation (10&11),

$$RMS\left[\Delta_{\beta u}\right] = \sqrt{F\left[\Delta_{\beta_u}^2\right] + \in} \tag{10}$$

$$\beta_{u+1} = \beta_u + \Delta_{\beta_u} \tag{11}$$

Where, RMS represents the root mean squared, β represents the constant variable, F represents the moving average value, and u parameter updates.

3.4.3 Mini Batch Stochastic Gradient Descent

In this section, Mini Batch Stochastic Gradient Descent (MBSGD) [16] is discussed. The proposed Mini Batch Stochastic Gradient Descent shows a quicker rate of convergence. The observation that the anticipated value of the gradient error determines the convergence rate and that a lower predicted term indicates a quicker convergence rate forms the basis of the theoretical analysis. The mini batch loss at iteration is given in equation (12),

$$m_u\left(N_u\right) = \frac{1}{c}\sum_{y=1}^{c} m\left(\Delta\left(Y_j^{u,y}, Y_k^{u,y}, Y_l^{u,y}\right)\right) \tag{12}$$

Where, m_u represents the iteration value, N represents the subset, c represents the sampling value, Y represents the estimator, u represents the batch size, k represents the distance metric, and y represents the loss function.

3.4.4 Rmsprop optimizer

In this section, Rmsprop optimizer (RPO) [17] is discussed. The momentum element included in RMSprop update rule helps to smooth out gradient changes and quickens convergence. This aids in resolving the issue of local minima or sluggish convergence. The optimizer for RMSprop sets a limit on the vertical oscillations. Thus, by taking larger steps in the upward way, we may raise the learning rate also enable the technique to come together more quickly. The result of the RMSprop computations is calculated as given in equation (13&14),

$$w_{ex} = \vartheta . w_{ex} + \left(1 - \vartheta\right) . ex^2 \tag{13}$$

$$w_{ex} = w_{ex} + (1-\vartheta).ec^2 \quad (14)$$

Where, w denotes the computation value, e denotes the population, x represents the convergence, and ϑ denotes the constant value. Weights, the square of the current value, and the prior value's average are used to create the new weighted average is calculated as given in equation (15),

$$X = X - \xi.\frac{ec}{\sqrt{w_{ex}} + \in} \quad (15)$$

Where, X represent the linear parameter. During the back ward propagation, the eX update the parameters as given in equation (16),

$$W = \wp - learning\ rate * eX \quad (16)$$

Where, W represent the back ward propagation. Rather of utilizing eX separately for every epoch in RMSprop, it uses the exponentially weighted averages of the squares of eX as given in equation (17),

$$T_{ex} = \vartheta * T_{ex} + (1-\vartheta) * eX^2 \quad (17)$$

Where, T represent the average weight. When comparing the algorithm such as Adaptive Gradient, AdaDelta, Mini Batch Stochastic Gradient Descent, and Rmsprop optimizer. The Rmsprop Optimization gives high accuracy which accurately identifies the Plant Leaf Disease.

By comparing other three optimization algorithms, Rmsprop Optimization (RPO) gives high accuracy which accurately classifies the Plant Leaf Disease. So, Rmsprop Optimization is used to optimize the weight parameters of RESNET152V2.

4. Result and Discussion

In this part, the trial outcomes of the indicated procedures are conversed. Python is used to carry out the suggested model on the Windows operating system. The models were trained with 8 GB of RAM also an Intel® Core (TM) i5 CPU. The hosting model is Streamlit Cloud - Streamlit is a popular open-source framework for building web applications with Python. Streamlit Cloud is a service provided by Streamlit for deploying and hosting these web applications for ML model. The trained PLDI-RESNET-RPO model is saved and deployed in the streamlit cloud for real time predictions. This study focused on a 64-bit Windows operating system. The obtained outcome of the proposed PLDI-RESNET-RPO technique is examined with the current methods like, CPL-DD-DNN [6], DLM-CDP-SWA [7], and PLDD-CV-MLA [8] individually. The Productivity outcome of suggested PLDI-RESNET-RPO technique is exposed in fig 2,

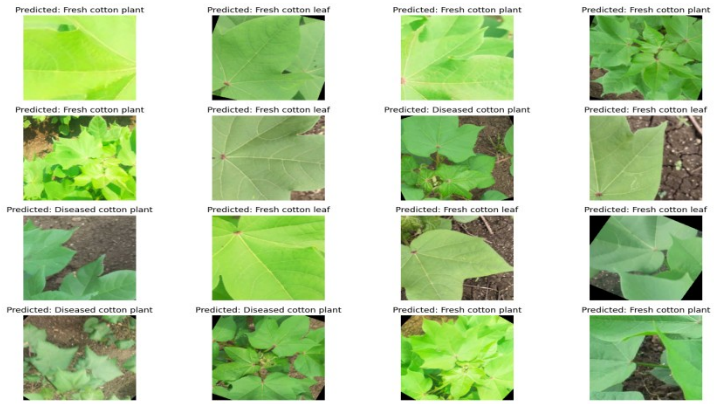

Figure 2: Output result of proposed PLDI-RESNET-RPO method

4.1 Performance measures

Accuracy and precision effectiveness of the suggested technique is described using performance measures.

4.1.1 Accuracy

It is the amount of total number of forecasts produced for a dataset divided by the count of precise forecasts. It is quantified using eqn (18),

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{18}$$

Where, TN signifies the true negative, TP signifies the true positive, FN denotes the false negative, and FP signifies false positive.

4.1.2 Training and Validation loss

A ML methods performance on training data is shown by its training loss. It is computed by computing the error among the methods projected values also real values in the training data. It is calculated as given in equation (19 & 20),

$$Training\ loss = (1/O) * \sum (z\_pred - y\_actual) \wedge 2 \tag{19}$$

$$validation\,loss = (1/O) * \sum (z\_pred - y\_actual) \wedge 2 \tag{20}$$

Where, O represents the number of data points, y_pred represents the forecast value, and y_actual represents the real value.

4.1.3 Training and Validation accuracy

In machine learning, training accuracy refers to a methods performance on training data. On the data used for training, it devices the methods effectiveness. It is calculated as given in equation (21&22),

$$training accuracy = (NCPITD/TNITD) * 100 \quad (21)$$

$$validation\ accuracy = (NCPIVD/TNIVD) * 100 \quad (22)$$

Where, $NCPITD$ represents number of properly expected instances on the training dataset, $TNITD$ represents total number of instances in the training data, $NCPIVD$ denotes number of correctly predicted cases on the validation data and $TNIVD$ represents total number of cases in the authentication dataset.

4.1.4 RoC

The RoC is an integrated measurement of a phenomena or outcome that may be measured. It is climbed by eqn (23),

$$RoC = 0.5 \times \frac{TN}{FP + TN} + \frac{TP}{FN + TP} \quad (23)$$

4.2 Performance Analysis

When evaluating the performance of various deep learning models for cotton plant disease classification, Table 1 summarizes the key performance metrics, including training loss, training accuracy, testing loss, and testing accuracy.

Table 1: Comparison of Various Models

Model	Training Data Loss	Training Accuracy (%)	Testing Data Loss	Testing Accuracy (%)
CNN	0.6912	73.81	0.8997	97.62
Inception V3	0.5157	94.87	0.0010	100.00
VGG16	0.9751	66.74	0.8098	77.78
VGG19	0.9751	66.74	0.8098	77.78
ResNet152V2	**0.2806**	**97.33**	**0.4829**	**100.00**

From Table 1, it is evident that ResNet152V2 outperforms other evaluated models across multiple performance metrics. ResNet152V2 achieves the lowest training loss (0.2806) among all models, indicating its strong capability to learn meaningful representations from the training data. A lower training loss reflects a smaller discrepancy between predicted and actual outputs, demonstrating effective learning. In terms of training accuracy, ResNet152V2 attains 97.33%, significantly outperforming traditional architectures such as VGG16 and VGG19 (66.74%) and the basic CNN model (73.81%). This highlights its superior feature extraction capability due to deep residual learning.

The model also demonstrates strong generalization performance, with a testing loss of 0.4829, which is considerably lower than that of CNN (0.8997) and VGG-based models (0.8098). This indicates that ResNet152V2 effectively avoids overfitting and maintains robustness on unseen data.

Furthermore, ResNet152V2 achieves a testing accuracy of 100%, matching the performance of Inception V3. However, Inception V3 exhibits an extremely low testing loss (0.0010), which may indicate potential overfitting or dataset bias. In contrast, ResNet152V2 maintains a more balanced trade-off between training and testing performance.

Overall, ResNet152V2 demonstrates a strong combination of:

- Low training and testing loss
- High training and testing accuracy
- Robust generalization capability

These characteristics confirm that ResNet152V2 is the most effective model among those evaluated for cotton plant disease classification. Its ability to learn complex patterns and generalize well makes it highly suitable for real-world agricultural applications.

Figure 3-6 shows stimulation outcomes of PLDI-RESNET-RPO proposed technique. Figure 6-8 depicts stimulation results of CPL-DD-DNN, DLM-CDP-SWA, and PLDD-CV-MLA existing methods.

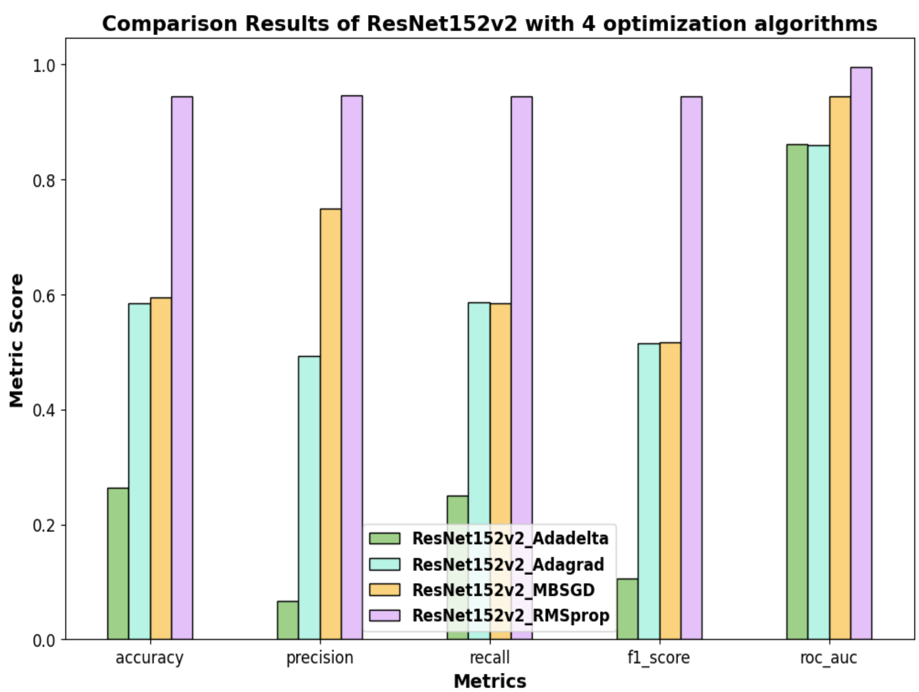

Figure 3: Performance analysis of comparison results of ResNet152v2 with 4 optimization algorithm

Figure 3 shows Performance analysis of comparison results of ResNet152v2 with 4 optimization algorithm. In contrast to a constant learning rate, RMSprop adjusts every parameter's learning rate by the gradient magnitudes, assisting in a faster and more seamless convergence. Here, the proposed ResNet152v2_ Adaptive Gradient attains 59.87% accuracy; 47.89% precision; 58.69% recall; 49.32% f1-

score; and 85.64% roc_auc. The ResNet152v2_AdaDelta attains 25.68% accuracy; 14.97% precision; 23.45% recall; 17.89% f1-score; and 85.79% roc_auc. ResNet152v2_Mini Batch Stochastic Gradient Descent attains 59.88% accuracy; 78.67% precision; 58.36% recall; 51.23% f1-score; and 94.12% roc_auc and ResNet152v2_Rmsprop optimizer attains 97.25%accuracy; 96.57% precision; 96.34% recall; 95.78% f1-score; and 99.21% roc_auc.

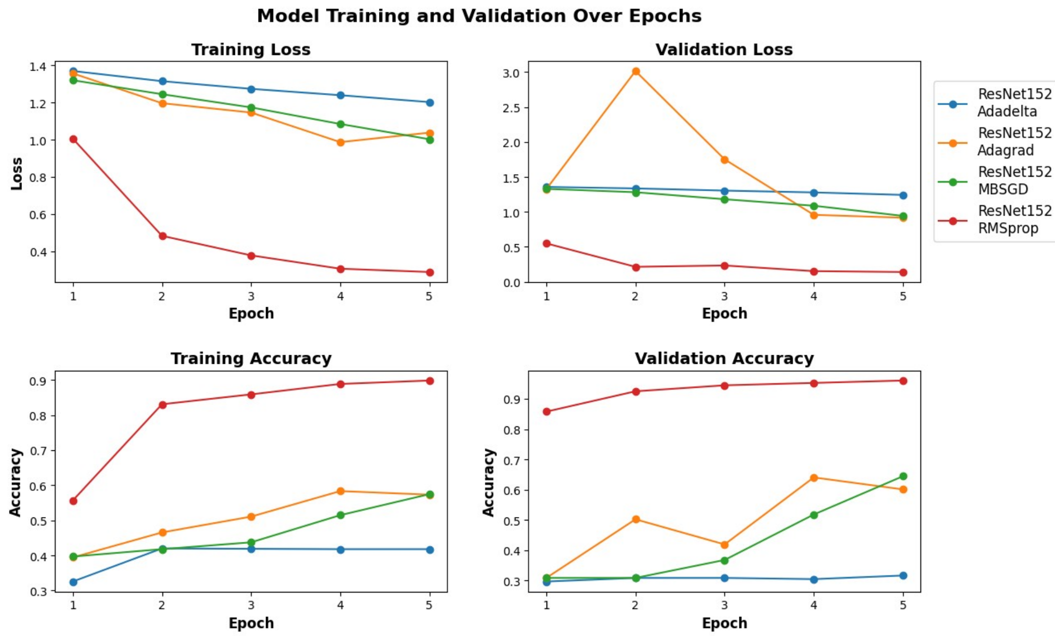

Figure 4: Performance analysis of model training and validation over epochs

Figure 4 shows model training and validation over epochs of the proposed Adaptive Gradient, AdaDelta, Mini Batch Stochastic Gradient Descent, Rmsprop optimizer method. The methods performance during training on the training dataset is gauged by the training loss. Here, the proposed Rmsprop optimizer method attains better Training also validation loss, and Training also validation accuracy.

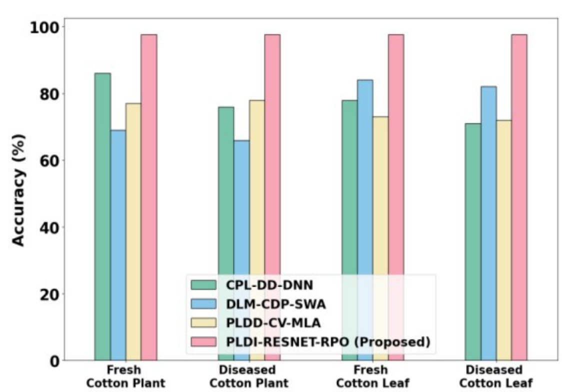

Figure 5: Performance analysis of Accuracy

Figure 5 shows Accuracy analysis. In contrast to a constant learning rate, RMSprop adjusts every parameter's learning rate by the gradient magnitudes, assisting in a faster and more seamless convergence. Here, the proposed PLDI-RESNET-RPO attains 25.68%, 22.54% and 31.24% higher accuracy for fresh cotton plant; 26.13%, 24.53% and 30.92% higher accuracy for diseased cotton plant; 29.83%, 27.46% and 20.98% higher accuracy for fresh cotton leaf; and 19.11%, 22.36% and 16.76% higher accuracy for diseased cotton leaf when compared to the existing as CPL-DD-DNN, DLM-CDP-SWA, and PLDD-CV-MLA respectively.

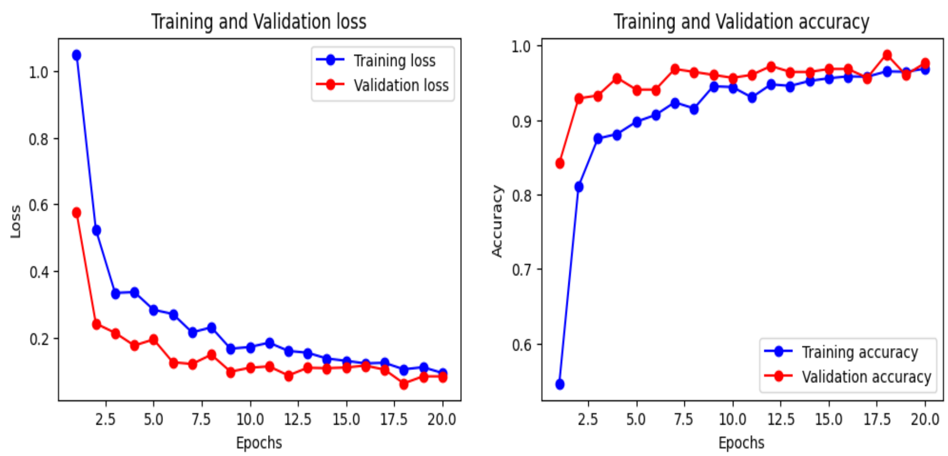

Figure 6: performance analysis of a) Training and validation loss, b) Training and validation accuracy

Figure 6 shows a) Training and validation loss, and b) Training and validation accuracy of proposed PLDI-RESNET-RPO method. The methods performance during training on the training dataset is gauged by the training loss. Here, the proposed PLDI-RESNET-RPO method attains better Training also validation loss, and Training also validation accuracy.

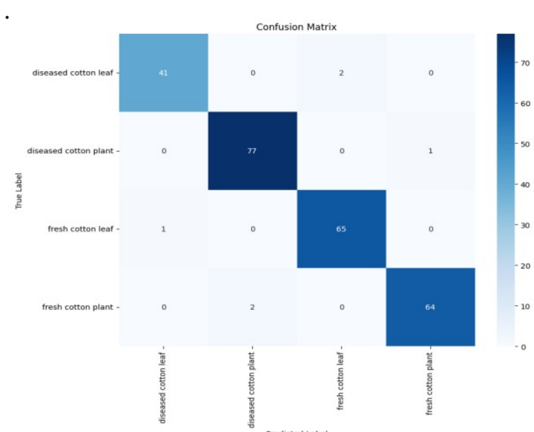

Figure 7: performance analysis of Confusion matrix

Figure 7 shows confusion matrix proposed PLDI-RESNET-RPO method.

Figure 8 shows RoC Analysis proposed PLDI-RESNET-RPO method. In the proposed method, the performance analysis of RoC entails assessing the algorithm's efficacy and efficiency in terms of its precision in identifying and categorizing items of interest. Here, the proposed PLDI-RESNET-RPO method attains better RoC.

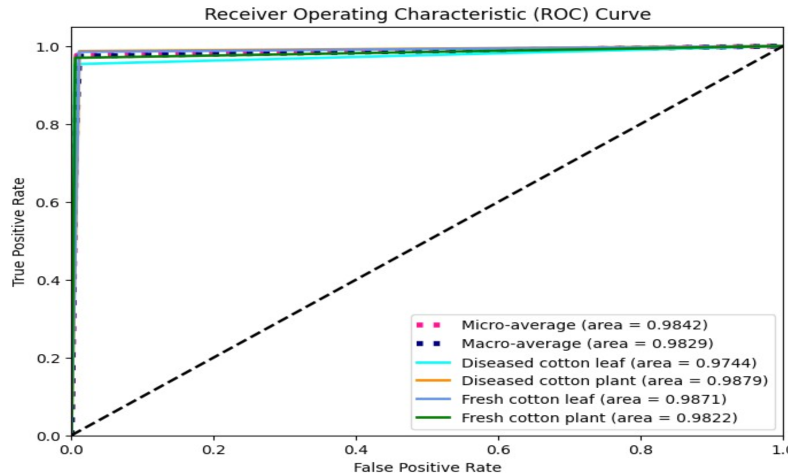

Figure 8: performance analysis of RoC

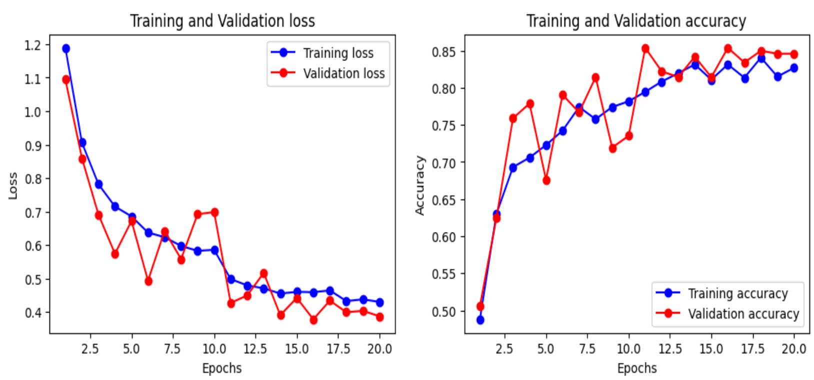

Figure 9: performance analysis of a) Training and validation loss, b) Training and validation accuracy

Figure 9 displays the routine analysis of a) Training and validation loss, b) Training and validation accuracy of the existing method CPL-DD-DNN. To track the model's learning progress, existing approaches generally depict the performance analysis of training also validation loss also accuracy across a series of epochs.

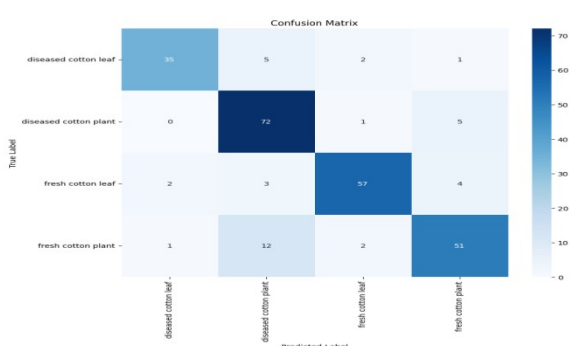

Figure 10: performance analysis confusion matrix

Fig 10 shows the performance study confusion matrix of existing technique CPL-DD-DNN.

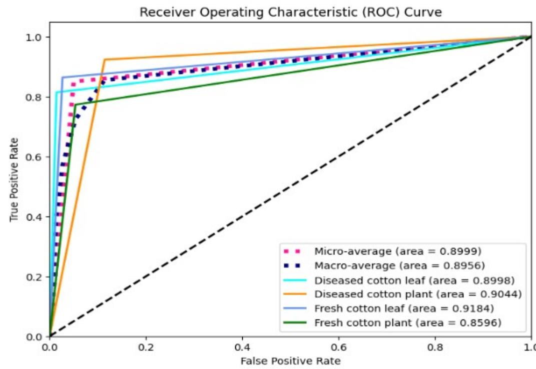

Figure 11: performance analysis of RoC

Figure 11 shows the performance analysis of RoC of the existing techniques such as CPL-DD-DNN, DLM-CDP-SWA, and PLDD-CV-MLA. The performance analysis of RoC entails assessing the algorithm's efficacy and efficiency in terms of its precision in identifying and categorizing items of interest.

The table 2 shows the performance analysis of each optimization algorithm.

Table 2: Performance analysis of each optimization algorithm

Methods	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**roc_auc**
Adaptive Gradient	59.87	47.89	58.69	85.64
AdaDelta	25.68	14.97	23.45	85.79
Mini Batch Stochastic Gradient Descent	59.88	78.67	58.36	94.12
Rmsprop optimizer	97.25	96.57	96.34	99.21

5. Conclusion

In this manuscript, PLDI-RESNET-RPO is successfully implemented. The PLDI-RESNET-RPO method proposes more accurate classification for identifying plant leaf disease than existing methods. The proposed PLDI-RESNET-RPO approach is used on the testing set; it produces results with a 99.49% accuracy rate and insignificant error rates, making it more productive and efficient than the current models. ResNet152V2 is used to organize the plant leaf infection. The performance of the proposed PLDI-RESNET-RPO approach contains attains 25.68%, 22.54% and 31.24% higher accuracy when related with existing methods like, CPL-DD-DNN, DLM-CDP-SWA, and PLDD-CV-MLA respectively.

Declaration on Generative AI

During the preparation of this work, the authors utilized Gemini to identify and rectify grammatical, typographical, and spelling errors. Following the use of this tool, the authors conducted a thorough review and made necessary revisions, and accept full responsibility for the final content of this publication.

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